ON THE NORMAL APPROXIMATION
FOR SUMS OF INDEPENDENT VARIABLES

BY

L. LE CAM*

TECHNICAL REPORT NO. 42
JANUARY 1985

*RESEARCH PARTIALLY SUPPORTED BY
NATIONAL SCIENCE FOUNDATION GRANT MCS80-02698

DEPARTMENT OF STATISTICS
UNIVERSITY OF CALIFORNIA
BERKELEY, CALIFORNIA
1. Introduction. In his famous monograph [1], Paul Lévy states a result that gives necessary and sufficient conditions for a sum 
\[ S = \sum_{j} X_j \] of independent variables to have an approximately normal distribution. The only condition imposed is the independence. There are no negligibility requirements. Lévy's statement and the accompanying arguments have sometimes been criticized as non-rigorous or too vague. Actually the statement makes perfect sense intuitively and the argument can be made rigorous. The present paper is an attempt to a rigorous presentation, following almost exactly the steps indicated by Lévy. A rigorous presentation, for the case where variances exist and converge to the variance of the limiting distribution, was given by Zolotarev in [5]. The general Normal case is covered by a paper of Mačys [3]. Zolotarev treats a more general problem in [6]. However, the techniques of proof are different from those used by Lévy. Here we consider the general case. In some lemmas we have used results that are more precise than those available to Lévy in 1937. However, these are inessential modifications of the main arguments. After some preliminaries, the theorem is stated in Section 2 below. Section 3 gives the proof of a number of auxiliary lemmas. Section 4 concludes the proof of the theorem.
2. Notation and results. Let $X_j; j = 1, 2, \ldots$ be a finite or infinite sequence of independent random variables and let $S = \sum_j X_j$ be their sum, assumed to exist if the sequence is infinite. The problem raised by Lévy is to find out conditions that imply that the distribution $\mathcal{L}(S)$ of $S$ is close to a Gaussian $\mathcal{N}(\mu, \sigma^2)$ distribution. For this to make sense one has to introduce distances between distributions. We shall use two of them: the Lévy distance $\lambda(P, Q)$ between the probability measures $P$ and $Q$ and the Kolmogorov vertical distance $\rho(P, Q)$. The distance $\lambda(P, Q)$ is the infimum of the numbers $\varepsilon$ such that

$$-\varepsilon + P((-\infty, x-\varepsilon]) \leq Q((-\infty, x]) \leq P((-\infty, x+\varepsilon]) + \varepsilon$$

for all values of $x$. The distance $\rho$ is given by

$$\rho(P, Q) = \sup_x |P((-\infty, x]) - Q((-\infty, x])|.$$  

The two are related by the inequalities

$$\lambda \leq \rho \leq \lambda + C(\lambda)$$

where $C(\lambda) = \min\{C_P(\lambda), C_Q(\lambda)\}$ with for instance $C_P(\lambda) = \sup_x P\{x, x+\lambda]\}$. We shall be concerned here with conditions that are necessary and sufficient for approximability of $\mathcal{L}(S)$ by $\mathcal{N}(\mu, \sigma^2)$ in the sense of the Kolmogorov distance. This distance is invariant by one to one monotone increasing transformations. Hence the size of $\sigma^2$ is unimportant. One can standardize and look for approximations by $\mathcal{N}(0, 1)$.

We shall often write $P \ast Q$ for the convolution of two measures $P$ and $Q$ and write $G_\sigma$ for the Gaussian measure $\mathcal{N}(0, \sigma^2)$.

One of the main results we need is a theorem conjectured by Lévy and proved by Cramér as follows.
THEOREM 1. Let the convolution $PQ$ be $\mathcal{N}(0,1)$ then there are numbers $\mu_i, \sigma_i$, $i = 1, 2$ such that $P = \mathcal{N}(\mu_1, \sigma_1^2)$ and $Q = \mathcal{N}(\mu_2, \sigma_2^2)$ with $\mu_1 + \mu_2 = 0$ and $\sigma_1^2 + \sigma_2^2 = 1$.

An easy consequence of Theorem 1 is a result proved by Lévy in [2].

THEOREM 2. There is a function $g$ on $[0,1]$ to $[0,1]$ with the following properties:

i) $g(\delta) > \delta$ and $g(\delta)$ decreases to zero as $\delta$ decreases to zero.

ii) If $G = \mathcal{N}(0,1)$ and $\lambda(PQ,G) \leq \delta$ then there is a $G_{\mu,\sigma} = \mathcal{N}(\mu, \sigma^2)$ such that $\lambda(P, G_{\mu,\sigma}) \leq g(\delta)$.

Now consider our sequence $\{X_j\}$ and let $\{X'_j\}$ be an independent replica of it. Let $S' = \sum_j X'_j$ and let $T = S - S'$. According to Theorem 2 and the bounds between Lévy and Kolmogorov distances recalled above, the sum $S$ will be approximately Gaussian if and only if $T$ is approximately Gaussian. Thus it will be sufficient to study the case where the independent variables $X_j$ have distributions that are symmetric around zero.

We shall make that assumption in the remainder of the present paper.

For our next statement we shall need a variant of Theorem 2 applicable to the symmetric case as follows.

THEOREM 2'. There is a function $f$ on $[0,1]$ to $[0,1]$ with the following properties:

i) $f(\delta) > \delta$ and $f(\delta)$ decreases to zero as $\delta$ decreases to zero.

ii) If $G = \mathcal{N}(0,1)$ and $P$ and $Q$ are probability measures symmetric around zero such that $\lambda(PQ,G) \leq \delta$ then there is a $\sigma$ such that for $G_{\sigma} = \mathcal{N}(0, \sigma^2)$ one has $\lambda(P, G_{\sigma}) \leq f(\delta)$. 
We are aware of results of Sapogov [4] that give bounds on the function \( g \). However we shall not use these bounds in order to show that Lévy's argument can be carried out without actual knowledge of the bounds, although the statements would be more precise if the bounds were used.

**THEOREM 3.** Let the variables \( X_j \) be independent symmetrically distributed around zero. Let \( D_j^2 = E(1 \wedge X_j^2) \). Then there are functions \( \varepsilon(\delta), \theta(\delta), \omega(\delta) \) all tending to zero as \( \delta \to 0 \) with the following properties. Let \( J \) be the subset of the integers where \( D_j^2 < \varepsilon(\delta) \). Then, if \( p[\mathcal{L}(S), G_j] < \delta \) one has

i) \( \sum_j \{ P(|X_j| > \theta(\delta); j \in J) \} < \omega(\delta) \).

ii) For each \( j \in J^C \) there is a Gaussian \( G_{\sigma_j} \) such that

\[
\sum_j \{ p(P_j, G_{\sigma_j}); j \in J^C \} < (64\pi)[f(\delta)]^{1/9}.
\]

This Theorem admits a converse. However to get a converse in terms of the Kolmogorov distance one must assume that \( \sum_j D_j^2 \) or something similar is not too close to zero. Here is such a converse.

**THEOREM 4.** Let the \( X_j \) be independent and symmetrically distributed around zero. Assume that for some subset \( J \) of the integers one has

i) \( \sum_j \{ P(|X_j| > \varepsilon); j \in J \} < \varepsilon \)

ii) For each \( j \in J^C \) there is a \( \sigma_j \) such that

\[
\sum_j \{ p(P_j, G_{\sigma_j}); j \in J^C \} < \varepsilon.
\]

Let

\[
\tau^2 = \sum_j \sigma_j^2; j \in J^C \} + \sum_j \{ E[\varepsilon \wedge X_j]^2; j \in J \}.
\]
Then

\[ \rho[\mathcal{L}(S), G_t] \leq K \frac{\varepsilon}{t} + 2\varepsilon \]

for a certain universal constant \( K \).

The combination of these two Theorems is what Lévy had stated in his own way: In order that \( \mathcal{L}(S) \) be close to \( \mathcal{N}(0,1) \) it is necessary and sufficient that i) any term that is not negligible be close to Gaussian and ii) the maximum of the negligible terms be itself negligible. Lévy seems to have been thinking of "nonnegligible" as something like our \( D^2_j \geq \varepsilon \) for a fixed \( \varepsilon \). Hence the number of nonnegligible terms has to stay finite. With the condition used here in Theorem 3 that \( D^2_j \geq \varepsilon(\delta) \), the number of such terms may tend to infinity as \( \delta \to 0 \). Hence the stronger formulation in terms of \( \sum_j \rho(P_1; G_{\sigma_j}) : j \in J^C \).
3. Auxiliary lemmas. As stated we assume that the variables $X_j$ are independent and symmetrically distributed around zero. We shall use a splitting technique described by Lévy in [1].

Let $(\xi_j, n_j, U_j, V_j)$ be independent random variables such that $\mathcal{L}(\xi_j) = \mathcal{L}(n_j)$ and $P(\xi_j = 1) = 1 - P(\xi_j = 0) = \alpha_j$. Assume that $X_j$ has the same distribution as $Y_j = (1 - \xi_j)U_j + \xi_jV_j$. The technique consists in replacing the sum $S = \sum Y_j$ by a sum $T = \sum (1 - n_i)U_i + \sum \xi_jV_j$, thus removing the difference $S - T = \sum (n_j - \xi_j)U_j$.

A splitting of $X_j$ in this form can be obtained in several manners. One possibility is to take numbers $\theta_j$ with $P(|X_j| > \theta_j) \leq \alpha_j$ and $\mathcal{L}(U_j) = \mathcal{L}(X_j | X_j < \theta_j)$, $\mathcal{L}(V_j) = \mathcal{L}(X_j | X_j > \theta_j)$. A more refined procedure would be to take independent variables $W_j$, uniformly distributed on $[-1, +1]$ and write that $X_j$ has the same distribution as a certain nondecreasing function $\varphi_j(W_j)$ such that $\varphi(-x) = -\varphi(x)$ for $x \geq 0$. One could then take $\xi_j = I[|W_j| > 1 - \alpha_j]$ and $\mathcal{L}(U_j) = \mathcal{L}(X_j | |W_j| < 1 - \alpha_j)$ and so forth.

**Lemma 1.** Let $(\xi_j, n_j, U_j, V_j)$ yield a splitting of $X_j$ as described. Assume that $\sup_j \alpha_j < \alpha$ and that the $U_j$ have symmetric distribution around zero. Then

$$\rho(\mathcal{L}(S), \mathcal{L}(T)) \leq 13\alpha^{1/3}$$

**Proof.** Take a number $\tau > 0$ and let $U_j = U_j' + U_j''$ where $U_j' = U_j$ if $|U_j| \leq \tau$ and $U_j' = 0$ otherwise. Let $\beta_j^2 = E(U_j')^2$. The variance of $\sum (n_j - \xi_j)U_j'$ is equal to $2 \sum \alpha_j(1 - \alpha_j) \beta_j^2 \leq 2\alpha(1 - \alpha) \sum \beta_j^2$. Using Chebyshev's inequality and taking account that
\[
\text{Pr}\left\{\sum_{j}(n_j - \xi_j)U_j \neq 0\right\} \leq 2\alpha(1-\alpha)\sum_j \text{Pr}\{|U_j| > \tau\}.
\]

one can write

\[
\text{Pr}\{\sum_{j}(n_j - \xi_j)U_j > \tau\} \leq 2\alpha(1-\alpha)D^2(\tau)
\]

where \(D^2(\tau) = \sum_j E\{1 \wedge \left|\frac{U_j}{\tau}\right|^2\}\). Thus

\[
\text{Pr}\{|S-T| > \tau\} \leq 2\alpha(1-\alpha)D^2(\tau).
\]

An application of standard inequalities for Kolmogorov distances and moduli of continuity yields

\[
\rho(S,T) \leq [\Gamma_S(\tau) \wedge \Gamma_T(\tau)] + 2\alpha(1-\alpha)D^2(\tau)
\]

where for instance \(\Gamma_S(\tau) = \sup_x \text{Pr}\{x < S \leq x+\tau\}\). According to Esseen's modification of Kolmogorov's concentration inequalities, one has

\[
\Gamma_T(\tau) \leq \frac{2\sqrt{2\pi}}{(\sqrt{1-\alpha})D(\tau)}.
\]

Now consider two cases. It may be that \(2\alpha D^2(0) \leq 13\alpha^{1/3}\). Then
\[
\text{Pr}\{\sum(n_i - \xi_i)U_j \neq 0\} \leq 2\alpha D^2(0)
\]
and the desired result follows. If on the contrary \(2\alpha D^2(0) > 13\alpha^{1/3}\), note that \(D^2(\tau)\) decreases continuously and tends to zero at infinity. Thus there is a smallest value \(\tau\) such that
\[
(1-\alpha)^3D^3(\tau) = \frac{\pi}{\alpha \sqrt{2}}.
\]
This value minimizes the expression

\[
2\left\{\frac{2\sqrt{2\pi}}{D(\tau)\sqrt{1-\alpha}} + \alpha(1-\alpha)D^2(\tau)\right\}
\]

the value of the minimum is

\[
4(2^{1/3} + 2^{-1/3})\pi^{1/3} \alpha^{1/3} \leq 13\alpha^{1/3}.
\]
This completes the proof of the lemma.

Now let us return to the Normal approximation with \( \rho[\mathcal{L}(S), \mathcal{N}(0,1)] \leq \delta \). According to the above we also have

\[
\rho[\mathcal{L}(T), \mathcal{N}(0,1)] = \gamma \leq \delta + 13\alpha^{1/3}.
\]

Thus we shall work with \( T \) instead of \( S \). Note that \( T \) is a sum of independent terms \( \sum_j (1-n_j)U_j + \sum_j \xi_j V_j \). Therefore Lévy's theorem can be applied to the sum \( \sum_j \xi_j V_j \).

**Lemma 2.** Let \( \gamma = \rho[\mathcal{L}(T), \mathcal{N}(0,1)] \). Assume \( 32f(\gamma) \leq 1 \) and assume that in the above splitting there is a subset \( J \) where the \( V_j \) are either identically zero or such that

\[
|V_j| \geq \theta = (1.6)(1 + \sqrt{2\log f(\gamma)})f(\gamma).
\]

Then \( \sum_{j \in J} \Pr\{\xi_j V_j > \theta\} \leq 4f(\gamma) \).

**Proof.** Let \( H \) be a subset of \( J \) where \( |V_j| \geq \theta \) and where \( n = \sum_{j \in H} \alpha_j \leq \frac{1}{2} \). Then, if \( W = \sum_{j \in H} \xi_j V_j \) one has \( \Pr[W = 0] \geq 1 - \sum \alpha_j \geq 1 - n \) and \( \Pr[|W| > \theta] \geq \sum_{j \in H} \sum_{k \neq j} (1-\alpha_k) \geq n(1-n) \).

According to the Cramér-Lévy theorem, there is a Gaussian \( \mathcal{N}(0,\sigma^2) = G_\sigma \) such that \( \lambda(\mathcal{L}(W),G_\sigma) \leq f(\gamma) \). Since \( \Pr[W = 0] \geq 1 - n \), such a Gaussian measure must be such that

\[
G_\sigma[-f(\gamma),f(\gamma)] \geq 1 - n - f(\gamma).
\]

However, here, \( n + f(\gamma) < \frac{1}{2} \). Therefore \( (1.6)f(\gamma) \geq \sigma \). Since \( \Pr[|W| > \theta] \geq n(1-n) \) one must also have

\[
G_\sigma([-\theta+f(\gamma),\theta-f(\gamma)]) \geq n(1-n) - f(\gamma).
\]
Using the usual upper bound on tail probabilities, this gives

\[ f(\gamma) + \sqrt{\frac{2}{\pi}} \frac{\sigma}{\theta-f(\gamma)} \exp\left\{ -\frac{1}{2\sigma^2} [\theta-f(\gamma)]^2 \right\} \geq \eta(1-\eta) \]

Here \( \theta \) is chosen so that

\[ \theta - f(\gamma) \geq (1.6)f(\gamma)\sqrt{2|\log f(\gamma)|} \geq \sigma\sqrt{2|\log f(\gamma)|} \]

Thus \( \eta(1-\eta) \leq 2f(\gamma) \) and \( n \leq 4f(\gamma) \), giving the required bound for the subset \( H \). Now note that \( 13\alpha^{1/3} \leq \gamma \leq f(\gamma) \). Thus \( \alpha \leq \left( \frac{f(\gamma)}{3} \right)^3 \). Thus any other element of \( J \) could be added to \( H \) without violating the condition \( n \leq \frac{1}{4} \). It must therefore be true that \( \sum_{j \in J} \alpha_j \leq 4f(\gamma) \).

This concludes the proof of the lemma.

**Lemma 3.** Let \( P \) be a probability measure such that \( \lambda(P,G_{\sigma}) \leq \varepsilon \) for \( G_{\sigma} = \mathcal{N}(0,\sigma^2) \). Then \( \rho(P,G_{\sigma}) \leq \varepsilon(1 + \frac{1}{2\sigma}) \).

**Proof.** For \( G_{\sigma} \) an interval of length \( \varepsilon \) has a probability at most \( \frac{1}{\sigma\sqrt{2\pi}} \varepsilon \).

**Lemma 4.** Let \( P_1 \) and \( P_2 \) be two probability measures. Let \( D^2(\tau) = \int (1 - (X_1)^2) dp_1 \). Then \( |D^2(\tau) - D^2(\tau)| \leq 2\rho(P_1,P_2) \).

**Proof.** Let \( P_1' \) be the distribution of \( (X_1)^2 \). Then \( \rho(P_1',P_2') \leq 2\rho(P_1,P_2) \). Furthermore, if \( P_1'' \) is the distribution of \( Y_1 = 1 - (X_1)^2 \), then \( \rho(P_1'',P_1') \leq \rho(P_1',P_2') \). Let \( F_1 \) be the cumulative distribution of \( Y_1 \). Then \( E_Y = \int_0^1 [1-F_1(y)] dy \). The result follows.

We shall need another inequality using the Lévy distance instead of the Kolmogorov distance.

**Lemma 5.** Let \( \lambda(P_j,G_{\sigma_1}) \leq \lambda \). Then \( 2\sigma_j^2 \geq D^2_j(1) - 2\lambda(1+\frac{1}{2}\lambda) \) with
\[ D_j^2(z) = E \left( \frac{X_j}{\tau} \right)^2 \] as usual.

**PROOF.** Let \( Z \) be a random variable with \( \mathcal{L}(Z) = G_\sigma \). Then for \( y > \lambda > 0 \) one can write \( \Pr[Z > y - \lambda] \geq P[X > y] - \lambda \) and a similar inequality for the negative tail of the distribution. Combining them, one obtains

\[ \Pr[|Z| + \lambda > y] \geq P[|X| > y] - 2\lambda, \]

or equivalently, for \( \lambda^2 < \nu \leq 1 \)

\[ \Pr\{(|Z| + \lambda)^2 > \nu\} \geq P\{1 \wedge |X|^2 > \nu\} - 2\lambda. \]

Integrating on \([0,1]\) gives

\[ \int_0^1 \Pr\{(|Z| + \lambda)^2 > \nu\} \, d\nu \geq \int_0^1 \Pr\{1 \wedge |X|^2 > \nu\} \, d\nu - 2\lambda - \lambda^2. \]

Integration by parts then yields

\[ E(|Z| + \lambda)^2 \geq E\{1 \wedge |X|^2\} - 2\lambda - \lambda^2. \]

However \( (|Z| + \lambda)^2 \leq 2(|Z|^2 + \lambda^2) \). Therefore

\[ 2E|Z|^2 \geq E(1 \wedge X^2) - 2\lambda - 3\lambda^2. \]

**LEMMA 6.** For \( S = \sum_j X_j \) assume \( \rho(\mathcal{L}(S), G) \leq \delta \). Fix an \( \epsilon > 0 \) and \( \lambda > 0 \). Let

\[ C(t) = \sqrt{\frac{2}{\pi}} \int_0^{\lambda^2} e^{-x^2/2} \, dx. \]

Assume \( C(t) > 2\delta \). Then the set of integers \( j \) such that \( D_j^2(t) \geq \epsilon \) has cardinality at most \( \frac{1}{\epsilon} \frac{8\pi}{[C(t) - 2\delta]^2} \).
PROOF. The concentration $\sup_x P[x \leq S \leq x+t]$ is at most
$$\frac{2\sqrt{2\pi}}{\sqrt{\sum_j D_j^2(t)}}.$$ The result follows.

LEMMA 7. Assume $\delta < .09$. Let $\epsilon$ be such that $\epsilon \geq 4f(\delta)[1+2f(\delta)]$. Let $J^c(\epsilon)$ be the set of indices $j$ such that $D_j^2(1) \geq \epsilon$. Then
$$\Delta = \sum_j \rho(p_j, \sigma_j): j \in J^c(\epsilon) \leq \frac{32\pi}{\epsilon} f(\delta)[1 + \frac{1}{\sqrt{\epsilon}}]$$
Also, for $0 < t < 1$ one has
$$\alpha = \sup_j P[|X_j| > t]: j \in J(\epsilon) \leq \frac{\epsilon}{t^2}.$$ PROOF. The last statement follows from Chebyshev's inequality. The first one is obtained as a combination of Lemma 5, Lemma 6 and Lemma 3.
4. Proof of Theorems 3 and 4. To prove Theorem 3, let 
\[ \varepsilon(\delta) = [f(\delta)]^{16/27}. \]
This gives a certain set \( J = J(\varepsilon) \). According to Lemma 7 and replacing \( 1 + \frac{1}{\sqrt{\varepsilon}} \) by \( \frac{2}{\sqrt{\varepsilon}} \), the sum \( \sum_j \{ \rho(P_j, G_{\sigma_1}) : j \in J^c \} \) does not exceed \( (64)^9 [f(\delta)]^{1/9} \).

Similarly, one can take \( \tau^2 = (13)^3 [f(\delta)]^{7/27} \). Then

\[ \alpha = \sup_j \{ P|X_j| \geq (13)^{3/2} [f(\delta)]^{7/54} : j \in J \} \leq \frac{1}{(13)^{3/2}} [f(\delta)]^{1/3}. \]

Thus \( 13\alpha^{1/3} \leq [f(\delta)]^{1/9} \). Let \( \gamma = \delta + [f(\delta)]^{1/9} \) and let \( \theta(\delta) \) be the maximum of \( (13)^{3/2} [f(\delta)]^{7/54} \) and \( (1.6)f(\gamma)(1+\sqrt{2}\log f(\gamma)) \). Now Lemma 2 says that

\[ \sum_j \{ P[|X_j| \geq \theta(\delta)] : j \in J \} \leq \omega(\delta) = 4f(\gamma). \]

This concludes the proof of Theorem 3.

To prove Theorem 4, let \( \sigma^2 = \sum_j \{ \sigma_j^2 : j \in J^c \} \) and \( \beta^2 = \sum_j \{ \mathbb{E}[e^{2X_j^2}] : j \in J \} \). Let \( V = \sum_j \{ X_j : j \in J^c \} \), \( W = \sum_j \{ X_j : j \in J \} \). Then \( \rho [\mathcal{L}(V), G_\sigma] \leq \sum_j \{ \rho(P_j, G_{\sigma_j}) : j \in J^c \} \leq \varepsilon. \) Also, if \( Y_j = [e^{X_j}] \text{sign } X_j \) and \( Z = \sum_j \{ Y_j : j \in J \} \) one will have \( \rho [\mathcal{L}(W), \mathcal{L}(Z)] \leq \varepsilon. \) Thus it is enough to bound the distance between \( G_\tau \) and the convolution of \( G_\sigma \) with \( \mathcal{L}(Z) \). For that one can use the procedure commonly employed to obtain the Berry-Esseen bounds. This will yield the result as stated, since the distance between \( G_\tau \) and \( G_\sigma \) convoluted with \( \mathcal{L}(Z) \) will take the form \( K \varepsilon \sum_j \{ \mathbb{E}[e^{X_j}]^2 : j \in J \} \frac{1}{\tau^3}. \)

Note that the bound will be usable only if \( \tau \) is large compared to \( \varepsilon. \) Note also that it would more pleasant aesthetically to use \( (\tau')^2 = \sigma^2 + \sum_j \{ D_j^2 : j \in J \} \) instead of the \( \tau^2 \) of the theorem. This can be done if for instance \( (\tau')^2 \geq 2\sqrt{\varepsilon}. \) Alternately, one could bound the Lévy distance \( \lambda [\mathcal{L}(S), G_{\tau_{1}^*}] \), instead of the Kolmogorov distance.
REFERENCES


17. DRAKER, D. C. (Feb 1983). Rank-based robust inference in regression models with several observations per cell.


32. BREIMAN, L. (May 1984). Nail finders, edifices, and Oz.


43. BICKEL, P. J. and YAHAV, J. A. (1985). On estimating the number of unseen species: how many executions were there?


56. LE CAM, L. and YANG, G. L. (January 1986). Replaced by No. 68.


64. O’SULLIVAN, F. (May 1986). Nonparametric Estimation in the Cox Proportional Hazards Model.


71. BICKEL, P.J. and YAHAV, J.A. (July 1986). Richardson Extrapolation and the Bootstrap.


77. O’SULLIVAN, F. (September 1986). Deconvolution of episodic hormone data.


82. DOKSUM, K.J. and LO, A.Y. (November 1986). Consistent and robust Bayes Procedures for Location based on Partial Information.


90. DABROWSKA, D.M. (March 1987). Rank tests for matched pair experiments with censored data.


95. CANCELLED


114. RITOV, Y. (September 1987). Estimation in a linear regression model with censored data.
118. ALDOUS, D.J. (October 1987). Meeting times for independent Markov chains.
120. DONOHO, D. and LIU, R. (October 1987, revised March 1988). Geometrizing rates of convergence, II.
127. Same as No. 133.
128. DONOHO, D. and GASKO, M. (December 1987). Multivariate generalizations of the median and trimmed mean II.
131. Same as No. 140
132. HESSE, C.H. (December 1987). A Bahadur - Type representation for empirical quantiles of a large class of stationary, possibly infinite - variance, linear processes
163. DIACONIS, P. and FREEDMAN, D.A. (June 1988). A singular measure which is locally uniform.
166. FAN, JIANQING (July 1988). Nonparametric estimation of quadratic functionals in Gaussian white noise.
172. ADLER, R.J. and EPSTEIN, R. (September 1988). Intersection local times for infinite systems of planar brownian motions and for the brownian density process.
Copies of these Reports plus the most recent additions to the Technical Report series are available from the Statistics Department technical typist in room 379 Evans Hall or may be requested by mail from:

Department of Statistics  
University of California  
Berkeley, California 94720

Cost: $1 per copy.